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The research on the fault detection based on the water level sensor network

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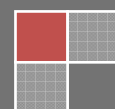
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ABSTRACT

This model makes use of the interface between the fault detection and fault isolation, which is theoretically employed by fault characteristic matrix. The matrix records the information of correlation between the detection signal and the fault as well as corresponding time. The state characteristics of the system can be reasoned from the relation between the fault signal and the fault. We can make full use of fault signals. The occurring time of the fault can be got by conducting the discrete time method on the observed fault signal. The application of the proposed detection method to the network of mine water level sensor proved that this method is more reasonable than the standard binary fault detection method.

KEYWORDS

Sensor; Fault detection; Interval observer; Robustness.



INTRODUCTION

For the guarantee of long-term reliability and security of mines, we can never afford to ignore the check of sensor failures. The principle of mine monitoring sensor is to utilize sensor feedback to construct the current mine environment. Should a detected signal from a fault sensor react in the feedback link of the control law, the consequences will be disastrous. Currently, common used methods of fault diagnosing and detecting of sensors are as follows: hardware redundancy method, the Kalman filter method, analytical redundancy method, neural network observing group method^[1]. Targeting at the fault detection of mine monitoring sensor, this paper adopts the interval observer as the estimator, thus combining the merits while overcoming the defects of hardware redundancy method and analytical redundancy method. Monitoring sensor is used to measure the various data for mine production process and it can input voltage signals, which are proportional to the amount of parameter content, into the controller. In this way, the monitoring sensor can deliver timely security status of the current environment. The predict accuracy by the monitoring sensor is of vital significance to workers' safety. The sensor is installed in the harsh underground environment of high-temperature, high-pressure, high humidity and it faces many uncertainties. Moreover, during the monitoring process, such factors as moisture, dust, and potential irresistible force may cause such faults as corrosion, filament fracture and loose contact of the sensor potentiometer, and deformation. All these can lead to relative serious error in measurement accuracy. Therefore, it is very necessary to carry out real time examination of the mine sensor. This paper takes the mine water level sensor as an example for analysis.

PRINCIPLES OF SYSTEM

The role of mine water level monitoring is to prevent sudden rise in mine water level resulting from such factors as floods and improve the performance of real-time monitoring. However, due to the complexity of the underground environment, these sensors are likely to undergo faults because of corrosion. If such faults can not be detected and isolated, the consequences would be disastrous. An effective detection method is online fault detection and isolation (FDI). There are two ways of solving the FDI problem: the hardware redundancy method (for complex environments such as the outer space), software redundancy law (applicable to large-scale monitoring system). Taking into account the cost and application environment, this paper selects the latter option. The application of the standard FDI encounters many shortcomings. This is mainly because of the adoption of the simple binary method for the interface between fault detection and fault isolation nature of fault signals. In order to improve the robustness of the model error, this paper proposes the interval observer method, in which information of fault characteristic matrix is added to the traditional dual structure. The information includes the residual fault sensitivity and residual time etc. The fault signal will be indicated in the form of discrete event sequence by the interval observer.

Traditional FDI method

According to a series of fault indication signals of residuals $r(k)$, the expression of $r(k)$ of the monitoring system of the fault detection and isolation (FDI) model can be shown as follows:

$$r(k) = \Psi(y(k), u(k)) \quad (1)$$

$u(k)$ and $y(k)$ are respectively stand for measurement input and measurement output and Ψ represents residual generating function, which can measure the input and output of the system at any time. In the ideal situation of no error, the residual value is zero. The occurrence of a fault depends on the relative value of each residual $r_i(k)$ in relation to the threshold, external interference, system uncertainties as well as noises. These measurements of residuals give birth to the fault characteristic $\phi(k) = [\phi_1(k), \phi_2(k), \dots, \phi_n(k)]$. The most simple method of observing fault signal comparing the residual and the threshold value:

$$\phi_i(k) = \begin{cases} 0, & \text{if } |r_i(k)| \leq \tau_i \\ 1, & \text{if } |r_i(k)| > \tau_i \end{cases} \quad (2)$$

The observed fault characteristics will be sent to the fault isolation module for isolation.

The binary relation between fault sequence $f(k) = [f_1(k), f_2(k), \dots, f_n(k)]$ and fault signal sequence $\phi(k)$ is called the binary fault characteristic matrix (FSM) theory. That is to say, when the value of an element of the matrix FSM_{ij} is one, it means that there is fault. However, such basic FDI mechanism has the following disadvantages: 1) τ_i must be able to conceive the uncertainties of the system according to the system input and output uncertainty and then conduct online self-adaptation. 2) Noise may generate chattering. 3) according to the fault characteristic matrix, the fault can only be detected in the case that it can be observed in the entire fault isolation stage; however, fault signals are dynamic in nature, so it can not

necessarily meet the above requirement. 4) Owing to the binary relation between fault and the fault signal, some useful information for improving resolution and accuracy may be lost.

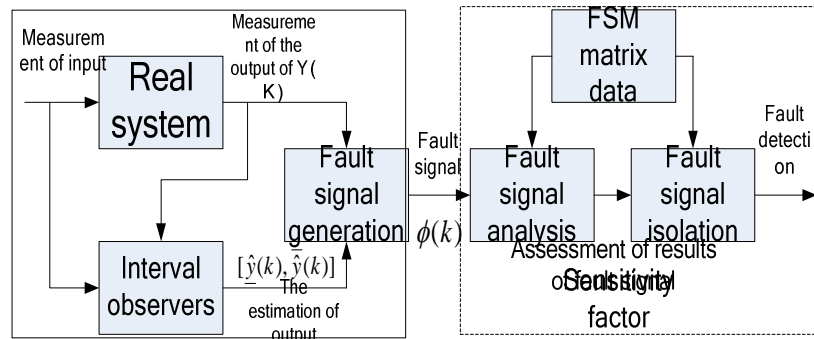


Figure 1 : Detection System of Fault h

Improved FDI method

The purpose of the fault detection is to produce fault signal for fault prediction. The fault detection algorithm should have guaranteed robustness, namely, able to deal with uncertainties. The robustness is determined by the comparison of the algorithm's sensitivity to fault and uncertainty (model error and interference). This paper adopts a passive algorithm and self-adaptive threshold in the decision-making stages so as to improve the robustness. Diagram 1 shows a general structure of this method.

The dynamic model of linear uncertain discrete time by FDI method for multi-input multi-output monitoring system can be illustrated as the subsequent formula:

$$\begin{aligned}
 x(k+1) &= A(\tilde{\theta})x(k) + B(\tilde{\theta})u_0(k) + F_a(\tilde{\theta})f_a(k) \\
 y(k) &= c(\tilde{\theta})x(k) + F_y(\tilde{\theta})f_y(k)
 \end{aligned}
 \tag{3}$$

Wherein, $y(k)$, $u_0(k)$, and $x(k)$ respectively represent system input, output, and state spatial vector; $A(\tilde{\theta})$, $B(\tilde{\theta})$, and $c(\tilde{\theta})$ are corresponding state, input and output matrixes; $\tilde{\theta}$ is the system parameter vector; $f_y(k)$ and $f_a(k)$ are faults happening to sensor and actuator; $F_y(\tilde{\theta})$ and $F_a(\tilde{\theta})$ are corresponding adjoint matrixes to $f_y(k)$ and $f_a(k)$.

The performance of the illustrated monitoring system based on interval model is realized by the linear observer. This model assumes that parameter θ is time-varying and it belongs to the interval $\Theta = \{\theta \in R \mid \underline{\theta} \leq \theta \leq \bar{\theta}\}$, which shows the uncertainty of the real system parameter $\tilde{\theta}$. The obtained interval observer can be expressed as follows:

$$\begin{aligned}
 \hat{x}(k+1) &= (A(\theta) - \Lambda c(\theta))\hat{x}(k) + B(\theta)u(k) + \Lambda y(k) \\
 \hat{y}(k) &= c(\theta)\hat{x}(k)
 \end{aligned}
 \tag{4}$$

u stands for the spatial state vector of system measuring input vector $\hat{x}(k)$ and $\hat{y}(k)$ is a vector for measuring the system output. The measurement system input and system real input in the following formula:

$$u(k) = u_o(k) + F_u(\theta)f_u(k)
 \tag{5}$$

$f_u(k)$ stands for input fault of the sensor and $F_u(\theta)$ is the corresponding adjoint matrix.

The design of the observer gain matrix Λ should ensure the stability of matrix $A_o(\theta) = A(\theta) - \Lambda C(\theta)$. The transient response of the uncertain parameter θ to the observer enables the interval observer to estimate the system output at any time; hence, each output $\hat{y}(k)$ is within the interval between $[\underline{\hat{y}}(k), \bar{\hat{y}}(k)]$:

$$\underline{\hat{y}}_i(k) = \min_{\theta \in \Theta}(\hat{y}_i(k)) \quad \bar{\hat{y}}_i(k) = \max_{\theta \in \Theta}(\hat{y}_i(k))
 \tag{6}$$

Such interval estimation can be obtained through numerical optimization algorithm^[3]; if there is no fault, the system output satisfies the following formula:

$$y_i(k) \in [\underline{\hat{y}}(k), \overline{\hat{y}}(k)] \quad (7)$$

Taking into account the initial condition, formula (4) can be rewritten into the input and output forms:

$$\begin{aligned} \hat{y}(k) &= G(q^{-1}, \theta)u(k) + H(q^{-1}, \theta)y(k) \\ &= G(q^{-1}, \theta)u_0(k) + H(q^{-1}, \theta)y(k) + G_{fu}(q^{-1}, \theta)f_u(k) \end{aligned} \quad (8)$$

Wherein

$$G(q^{-1}, \theta) = C(\theta)(qI - A_o(\theta))^{-1}B(\theta) \quad (9)$$

$$H(q^{-1}, \theta) = C(\theta)(qI - A_o(\theta))^{-1}\Lambda \quad (10)$$

$$G_{fu}(q^{-1}, \theta) = G(q^{-1}, \theta)F_u(\theta) \quad (11)$$

The expression of residual is as follows:

$$r(k) = y(k) - \hat{y}(k) \quad (12)$$

According to formula (8), the residual expression can be shown as follows:

$$r(k) = -G(q^{-1}, \theta)u(k) + (I - H(q^{-1}, \theta))y(k) \quad (13)$$

The formula of unknown input impact can be obtained with the help of formulae (8), (12), and (13):

$$\begin{aligned} r(k) &= r_\theta(k) + (I - H(q^{-1}, \theta))(G_{fa}(q^{-1}, \tilde{\theta})f_a(k) \\ &\quad + G_{fy}(q^{-1}, \tilde{\theta})f_y(k) - G_{fu}(q^{-1}, \theta)f_u(k) \end{aligned} \quad (14)$$

Wherein:

$$r_\theta(k) = -G(q^{-1}, \theta)u_0(k) + (I - H(q^{-1}, \theta))y_0(k) \quad (15)$$

$$G_{fa}(q^{-1}, \tilde{\theta}) = C(\tilde{\theta})(qI - A(\tilde{\theta}))^{-1}F_a(\tilde{\theta}) \quad (16)$$

$$G_{fy}(q^{-1}, \tilde{\theta}) = F_y(\tilde{\theta}) \quad (17)$$

When the residual is not influenced by system faults but only by structural uncertain parameters, the formula can be written as $r_\theta(k)$. In this case, we consider the passive impact of uncertain parameters on the robustness. Estimate the residual and use the interval observer of formula (4) to get the nominal model $\hat{y}^o(k, \theta^o)$; make $\theta = \theta^o \in \Theta$; then comes the residual estimation formula:

$$r^o(k) = y(k) - \hat{y}^o(k) \quad (18)$$

In the ideal situation of no error, the value of $r^o(k)$ shall be zero. However, due to the unknown input disturbance and model error, this assumption was not solid. Error will spread from interval observer to residual makes nominal residual in the interval changes:

$$[\underline{r}_i^o(k), \bar{r}_i^o(k)] \tag{19}$$

Wherein: $\underline{r}_i^o(k) = \hat{y}_i(k) - \hat{y}_i^o(k)$ $\bar{r}_i^o(k) = \bar{y}_i(k) - \hat{y}_i^o(k)$ (20)

$\hat{y}_i(k)$ and $\bar{y}_i(k)$ are estimated minimum and maximum output value of system i according to formula (6). The interval given by formula (19) can be viewed as adaptive threshold value:

PRODUCTION OF FAULT SIGNAL

The measuring noise of the sensor can lead to unstable shaking. The gradual reasoning method can avoid the shaking^[4]. Apply the Cramer equation on each residual and then the fault detection signal can be showed as follow:

$$\phi_i(k) = \begin{cases} \frac{(r_i^o(k)/\bar{r}_i^o(k))^4}{1 + (r_i^o(k)/\bar{r}_i^o(k))^4}, & \text{if } r_i^o(k) \geq 0 \\ -\frac{(r_i^o(k)/\bar{r}_i^o(k))^4}{1 + (r_i^o(k)/\bar{r}_i^o(k))^4}, & \text{if } r_i^o(k) \leq 0 \end{cases} \tag{21}$$

Formula (21) transform residual into step-by-step form,

$\phi_i(k) \in [-1, 1]$. When $|\phi_i(k)| \geq 0.5$, it is assumed as a fault signal; otherwise, no fault signal.

Dynamic nature of fault signal

The dynamic characteristic of the fault signal $\phi_i(k)$ can be shown by the comparative sensibility of residual $r_i(k)$ to fault f_j . According to reference^[5], the residual sensitivity can be expressed as follows:

$$S_f(q^{-1}) = \frac{\partial r}{\partial f} \tag{22}$$

Therefore, the residual sensibility is the transfer function of the impact of fault to residual. This concept is of great importance to the quality fault detection and occurring time of fault.

With formula (14) and formula (22), we can obtain the residual sensitivity of f_y, f_u , and f_a .

$$S_{f_y}(q^{-1}, \theta) = (I - H(q^{-1}, \theta))G_{f_y}(q^{-1}, \tilde{\theta}) \tag{23}$$

$$S_{f_u}(q^{-1}, \theta) = -G(q^{-1}, \theta)F_u(\theta) \tag{24}$$

$$S_{f_a}(q^{-1}, \theta) = (I - H(q^{-1}, \theta))G_{f_a}(q^{-1}, \tilde{\theta}) \tag{25}$$

S_{f_y}, S_{f_u} and S_{f_a} are respectively the fault sensitivity of f_y, f_u , and f_a .

Substitute formulae (23) — (25) into formula (14), and we can obtain the formula for residual sensitivity:

$$r(k, \theta) = r_\theta(k, \theta) + S_{f_a}(q^{-1}, \theta)f_a(k) + S_{f_y}(q^{-1}, \theta)f_y(k) + S_{f_u}(q^{-1}, \theta)f_u(k) \tag{26}$$

Design of fault detection and isolation

Normally, fault detection and fault isolation are two separate modules. The typical interface of these modules will conduct binary analysis with the fault error produced by the residual. The integration of these two modules is very hot in recent years^[6]. On one hand, the dynamic characteristic of the fault signal produced by special faults depends mainly on the dynamic characteristics of the generator in the fault detection. On the other hand, the fault detection exerts great influence on

the fault isolation. In order to accurately measure the fault, fault detection and fault isolation can't be separately considered. If we adopt the observer as fault detector, the observer gain matrix will greatly influence the dynamic characteristics of the residual generator. Hence, theoretically, the dynamic characteristics of fault signal sequence will also influenced by the gain impact of observer.

The design of interface adds more characteristics information of the fault signal on the basis of fault characteristic matrix (FSM) theory. This method deploys different fault feature matrixes: Bult attribute (FSM_{01}), fault residual sensitivity characteristic (FSM_s), occurring sequence characteristics (FSM_o), and occurring time occurrence (FSM_t). Those matrixes store the information of impact of fault on residual set. The nest introduces the method of obtaining the above matrix by using the interval observer model.

FSM_s : evaluate the fault signal sensitivity and describe the degree of residual i exceeds the threshold caused by fault f_j within the interval shown in (19). Therefore, according to the internal form (26) of the threshold, FSM_s should be proportional to the residual sensitivity function $S_f(q^{-1})$ and inversely proportional to $\bar{r}_i^o(k)$ or $\underline{r}_i^o(k)$. The estimation formula of FSM_s is as follows:

$$FSM_s = \begin{cases} \frac{S_{ri,ff}(q^{-1})\eta(k-t_0)}{|\bar{r}_i^o(k)|}, & \text{if } r_i^o(k) \geq 0 \text{ and } k \geq t_0 \\ \frac{S_{ri,ff}(q^{-1})\eta(k-t_0)}{|\underline{r}_i^o(k)|}, & \text{if } r_i^o(k) < 0 \text{ and } k \geq t_0 \\ & \text{if } k < t_0 \end{cases} \tag{27}$$

Wherein, $\eta(k)$ is step-input and $S_{ri,ff}(q^{-1})$ is the relative sensitivity of normal residual to fault f_j .

The consistency of the observed fault signal sequence $\phi_i(k)$ and the FSM_s of the theoretical fault j can be shown by f_s . There exists i that can make FSM_s zero. When $|\phi_i(k)| \geq 0.5$, $f_s = 0$. Otherwise, the expression of f_s is as follows:

$$f_s = \frac{|\sum_{i=1}^{ny} (\phi_i(k) FSM_s)|}{\sum_{i=1}^{ny} |FSM_s|} \tag{28}$$

The fault signal observed by sensitivity factor decides whether the final detection fault assumption establish or not. For example, Bult attribute:

$$FSM_{01} = \begin{cases} 1, & FSM_s \neq 0 \\ 0, & FSM_s = 0 \end{cases} \tag{29}$$

FSM_t : evaluate the occurring time of fault signal; in time of fault, the fault signal should appear at different times.

$$FSM_t = \begin{cases} [\varphi_{ij}, \bar{\varphi}_{ij}], & \text{if } S_{ri,ff}(q^{-1}) \neq 0 \\ [-1,1], & \text{if } S_{ri,ff}(q^{-1}) = 0 \end{cases} \tag{30}$$

The sequence of fault occurring:

$$FSM_o = \begin{cases} \sigma, & \delta_j(\sigma) = \bar{\varphi}_{ij} \text{ and } FSM_t \neq [-1,1] \\ 0, & FSM_t = [-1,1] \end{cases} \tag{31}$$

δ_j is the non-repetitive φ_{ij} contained in row j in ascending order. Its value can't enable that be 1. Through the comparison of the observed information and stored matrix FSM , we can get the corresponding sensitivity factor f_{01} , f_t and f_o of FSM_{01} , FSM_t and FSM_o . And then carry out weights summation on each sensitivity factor. In this way, we can predict the possibility of fault.

SIMULATIONS

The residual sensitivity of the water level change sensor measurement parameters can be demonstrated as follows^[8]:

$$\begin{aligned} \dot{x}(t) &= a(t)x(t) + b(t) \\ y(t) &= x(t) + p_y(t) \end{aligned} \tag{32}$$

In the above formula: $x(t)$ refers to the input parameter of the sensor; $y(t)$ is the sensor output parameter; $p_y(t)$ stands for the measured interference noise signal; $a(t)$ and $b(t)$ are nonlinear function values of other measuring parameters; here we ignore their concrete forms; as functions a and b are uncertain, set $a = \hat{a} + \rho_a$ and $b = \hat{b} + \rho_b$. Here \hat{a} and \hat{b} are known nominal values.

The calculation algorithm of residue is composed of alarm condition and threshold value. If the residual is greater than the threshold value and the sensitive factor condition is met, it will produce an alarm.

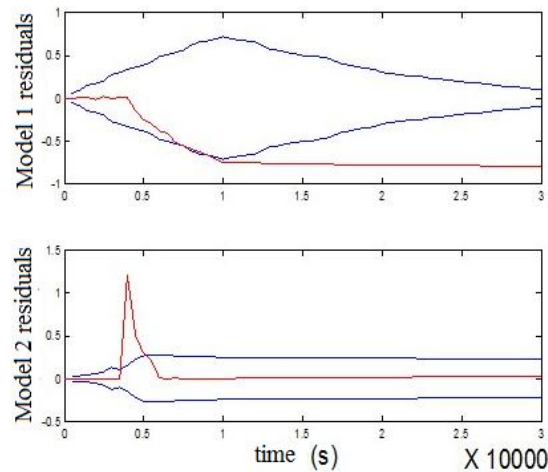


Figure 2 : Variation of residual and adaptive threshold with time

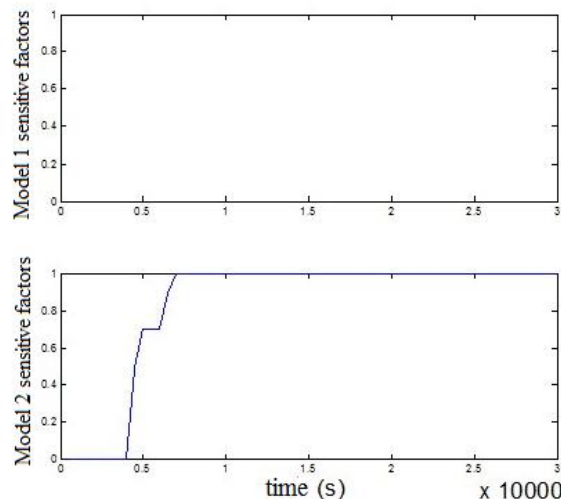


Figure 3 : Variation of sensitivity factor with time

When $t_0 = 4000s$, fault occurs in model 2. At that time, the gain of the observer in model 2 is adjusted to 0.5 while that of model 1 is adjusted 0.01. Diagram 2 shows residual of these two models and the corresponding adaptive residuals. According to the stored information of fault characteristic matrix, the fault of model 2 was first detected, but the detected fault signal will disappear over time. While the signal of model 1 is in line with the fault observed signal. In this kind of circumstance, the fault isolation method will take model 1 as the fault detection results. The application of traditional method may engender wrong choices. Diagram 3 shows the corresponding sensitivity of these two models. From the above, we can learn that the dynamic characteristics proved that model 2 has no fault despite the fact that the signal duration of it is not long.

CONCLUSIONS

This paper presents an optimal fault detection method for mine water level sensor. It makes up the shortcomings of the traditional method in fault detection, considers the dynamic nature of the fault signal, and then makes the correct judgment with the help of fault characteristic matrix. The application of this method to multi-fault and various sensor models would be the focus of future research.

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